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ABSTRACT

In general, most human physiological organs systems, which are constructed by collecting more than one part to perform either single or multiple functions. In addition, the successive times between failures are not necessarily identically distributed. More generally, they can become smaller (an indication of deterioration). However, if any organic deterioration is detected, then the decision of when to take the intervention, given the costs of diagnosis and therapeutics, is of fundamental importance. At the time of the decision, the degree of future human organic deterioration, which is likely to be uncertain, is of primary interest for the decision maker (for example, determining the prevalence of disease, doing a population survey, or measuring the level of a toxin). This paper develops a possible structural design of decision support systems by considering the sensitivity analysis as well as the optimal prior and posterior decisions. The proposed design of Bayesian decision support systems facilitates the effective use of the computing capability of computers and provides a systematic way to integrate the expert's opinions and the sampling information which will furnish decision makers with valuable support for quality decision-making.

Keywords: Aging Chronic Diseases; non-homogeneous Poisson process (NHPP); Bayesian Decision Theory; Decision Support Systems.

1. INTRODUCTION

Demographic shifts in the population will lead to a further increase in the proportion of elderly and consequently of people with chronic diseases. For example, almost 75 percent of the elderly (age 65 and over) have at least one chronic. About 50 percent have at least two chronic diseases [5]. In addition, aging is a strong socially appealing issue with many implications for users as well as providers of healthcare. In general, most human physiological organs, which are constructed by collecting more than one part to perform either single or multiple functions. However, the successive times between failures are not necessarily identically distributed. More generally, they can become smaller (an indication of deterioration). If any organic deterioration is detected, then the decision of when to take the intervention, given the costs of treatments and failures, is of fundamental importance. At the time of the decision, the degree of future organic deterioration, which is likely to be uncertain, is of primary interest for the decision maker. Naturally, gathering additional data will not always be economical. It is of special interest to determine analytically or numerically the conditions under which it will be worthwhile to collect additional information. Therefore, we propose a Bayesian decision process to provide a significantly improved methodology for dealing with the decision problems of physiological organs systems which can determine the conditions for taking the different actions, and thereby help the decision-maker maximize expected profit (or minimize expected loss).

2. MODELS FOR DESCRIBING AGING

In order to model aging in chronic diseases, the non-homogeneous Poisson process (NHPP) was introduced since it seems more plausible for human physiological system consisting of many organs. The system failure process is time-dependent and its intensity function of the failure process is assumed to be of the form $\lambda(x)=\lambda_0 h(\beta;x)$, where λ_0 is the scale factor, β is the aging deteriorating rate, x is the elapsed time, and $h(.)$ can be any function that reflects the deteriorating process. Suppose that the system has a planned lifetime (i.e., time horizon) T and let the decision has to be made at time t. The crucial two-action decision is whether at time t, the failure rate of the system will be too high (in which case some risk reduction action needs to be taken), or whether it will still be within an acceptable range (in which case we can keep operating the system according to the status quo). Another option is to gather additional information before the final decision is made.

Bayesian decision analysis has been well developed for decades [3,18], especially in the fields of statistical decisions [2,7], reliability engineering [4,9]), quality management[1,16], and decision science [6,15]. The basic elements of the Bayesian decision process are as follows:

(a) Parameter space Θ:{(λ_0,β)| λ_0>0},where λ_0 is the scale factor and β is the deterioration rate. Both parameters are uncertain and can be estimated through experts' opinions.

(b) Action space A:{a_1,a_2}, where a_1 is the status quo, and a_2 is the risk reduction action. (We eventually expand this to consider a third possible action, the collection of additional information).

(c) Loss function L: a real function defined on $\Theta\times A$. If we decide to keep the system operating, then the loss we face is $L(\theta,a_1)$; if we decide to take the risk reduction action, then the loss we face is $L(\theta,a_2)$.

(d) Sample space S : The additional information available to be collected. For example, the successive failure times till the n. failure can be denoted as the likelihood function of the form

$$f_{X_1,X_2,\cdots,X_{n^*}}(x_1,x_2,\cdots,x_{n^*})=[\prod_{i=1}^{n^*}\lambda(x_i)]\,exp(-\Lambda(x_{n^*})] \quad (1)$$

where $\Lambda(x)=\int_0^x\lambda(u)du$ is the mean number of failures by time x in the NHPP. The cost of collecting this additional information should also be reflected in the decision process.

The following terminology will be used throughout this paper:

C_A: the cost of a failure if it occurs.

C_R: the cost of the proposed risk reduction action.

C_I: the cost of collecting additional information.

ρ: the reduction in failure rate that would result from the proposed risk reduction action ($0<\rho<1$).

M: the expected number of failures during the time period $[t,T]$ under the status quo.

The decision variable we are dealing with is then the expected number of failures during the time period $[t,T]$, i.e.,

$$M\equiv M(T,t,\lambda_0,\beta)=\int_t^T\lambda(s)ds \quad (2)$$

Note that the expected number of failures M is itself a random variable, since it is a function of the two uncertain parameters λ_0 and β, and this is the case where Bayesian analysis can be effectively performed. Suppose that the risk reduction action will reduce the failure intensity by a fraction ρ, where $0<\rho<1$, then the expected number of failures in [t ; T], if the risk reduction action is taken is given by

$$\int_t^T\lambda(s)(1-\rho)ds=(1-\rho)\,M. \quad (3)$$

On the basis of the assumptions given above, we therefore have a two-action problem with a linear loss function, where the loss for taking action a_1 (i.e., continuing with the status quo) is C_AM and the loss for taking action a_2 (i.e., undertaking the risk reduction action) is $C_A(1-\rho)M+C_R$. The expected loss for the status quo is simply $C_A\boldsymbol{E}\{M\}$, and the expected loss for the risk reduction action is $C_A(1-\rho)\boldsymbol{E}\{M\}+C_R$. A natural conjugate prior for the power-law failure model proposed in [10] is given by

$$f(\lambda_0,\beta)=K'\lambda_0^{\,m-1}\beta^{m-1}[\exp(-\alpha)y_m^{\,m}]^{\beta\text{-}1}\exp(-\lambda_0 c y_m^{\,\beta}) \quad (4)$$

and also a natural conjugate prior for the exponential failure model proposed is given by

$$f(\lambda_0,\beta)=K''\lambda_0^{\,m}exp\left(\beta\alpha(m+1)y_m-\lambda_0 c\frac{exp(\beta y_m)-1}{\beta}\right) \quad (5)$$

where K' and K'' are the normalizing constants, and the parameters c and α can be chosen to give the desired values of expectations for λ_0 and β, respectively, and the parameters m and y_m can be chosen to give the desired degrees of dispersions for λ_0 and β, respectively [10,11,12,13]. Both the natural conjugate priors allow for dependence between λ_0 and β and have relatively simple closed-form expressions for their moments. Furthermore, the joint prior distribution about λ_0 and β in the Bayesian decision process can be straightforwardly derived.

3. THE DECISION SUPPORT SYSTEM

The Bayesian decision process mentioned in the previous section is capable of not only dealing with the uncertainties but also taking into account prior knowledge. However, this process cannot be easily performed; in particular, it requires the technology of numerical integration for carrying out complicated computations. To deal with the problem and to provide decision makers an efficient information system as well, we proposed a structural design of DSS to assist decision makers in making optimal decisions of minimum losses for deteriorating systems.

According to the interpretations about effective and efficient DSSs from [8,20], several required functions should be included in our study. First, the DSS needs to provide the optimal prior decision without using failure data for Bayesian updating. In such a case, the decision is based only on the uncertainties quantified by decision makers. Secondly, the DSS has to notify the decision maker whether collecting additional information is desirable or not. In some cases, the decision maker might not be confident or comfortable about the prior decision since the prior information is too vague. Therefore, collecting failure data could be another alternative before making the final decision. Furthermore, the DSS also needs to provide the optimal posterior decision. It should integrate the quantified prior information and the collected failure data. Finally, the DSS should have the ability to perform sensitivity analysis about each uncertain factor since decision makers might not be satisfied with the numerical values they applied in the system. The DSS has to allow decision makers change each uncertain entity (e.g. deteriorating rate), and therefore derives a range of such uncertain entities within which the optimal decision remains unchanged. Also, the ability of performing what-if analysis is crucial for the DSS [14,17,19]. It is of important interest for decision makers to see what the resulting decision will be once they change some parameters. According to the discussion above, the inputs to the DSS would be the uncertainties mentioned previously and the failure data (if available), and the outputs would be the optimal prior decision, the optimal posterior decision, and the results of the sensitivity analysis and what-if analysis. In order to perform the required complicated numerical integration for the decision process, the specifications of hardware and software should be closely considered. The hardware should have the ability to correctly and quickly respond to decision makers before they get impatient and the software should be easily and reliably programmed and maintained.

The DSS includes three major processes, which are decision derivation, sensitivity analysis, and what-if analysis, respectively. These processes along with the information database are the essence of the DSS. Figs. 1 and 2 show the system follow chart and the system framework of the DSS, respectively [14]. The DSS has input, output, and process three major parts. The detailed information descriptions of each part are as follows:

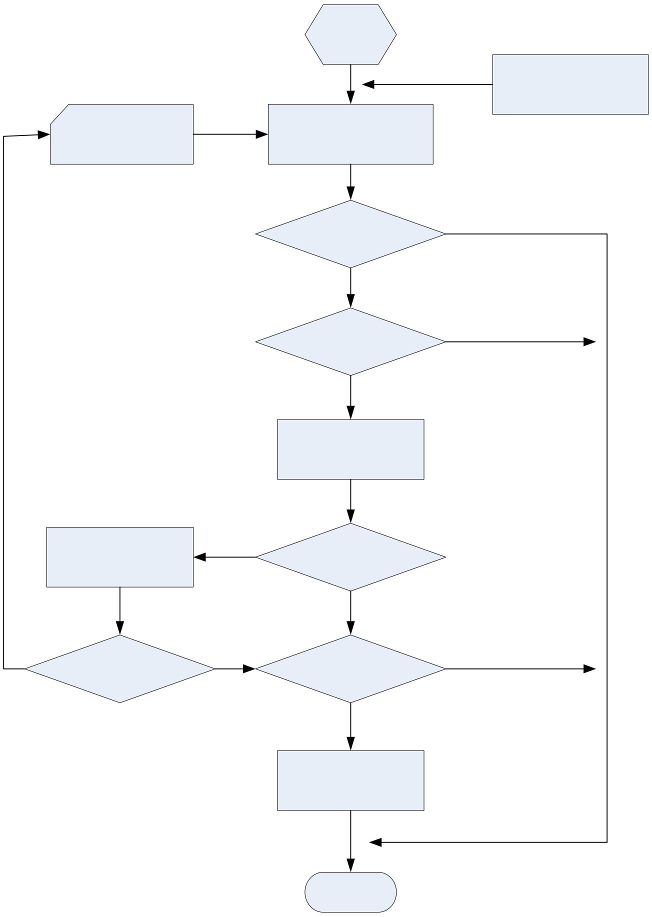

Fig.1. System follow chart of the DSS.

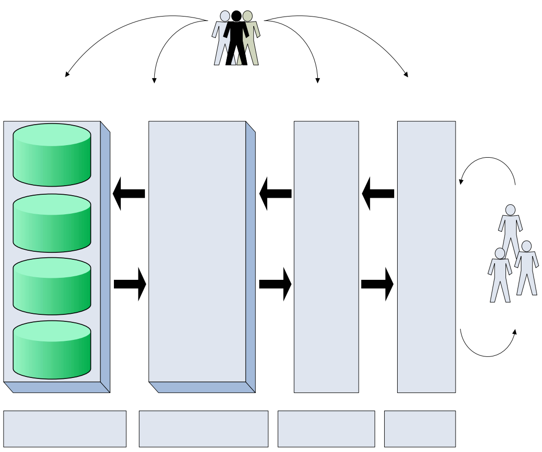

Fig.2. The system framework of the DSS.

Prior information part: The prior information has eleven elements and are described as follows:
(1) *System lifetime*: The expected performing time of the physiological organs systems. (the measuring unit would be year.)
(2) *Initial service date*: The date that the physiological organs systems first start.
(3) *Decision time*: The actual time for decision makers to make the decision of whether maintaining the status quo or undertaking a risk reduction action.
(4) *Cost of failure*: The cost or loss once the failure actually occurs.
(5) *Cost of risk reduction action*: The cost for undertaking the risk reduction action.
(6) *Risk reduction factor*: The fraction of the original function of the system that the risk reduction action can retrieve.
(7) *Cost of collecting information*: The cost of collecting the failure data.
(8) *E{Scale Factor}*: The expected value of the scale factor.
(9) *SD{Scale Factor}*: The standard deviation of the scale factor.
(10) *E{Deterioration Rate}*: The expected value of the deterioration rate.
(11) *SD{Deterioration Rate}*: The standard deviation of the deterioration rate.

Sampling information part: The sampling information is for inputting the observed failure data.

Decision part: The decision part provides the optimal decisions that are suggested by the DSS. There are five output elements that can be valuable to decision makers for making the final decision. We introduce them as follows:
(1) *Expected value of sampling information (EVSI)*: The EVSI can be treated as an indicator for determining whether to collect the failure data. In particular, if the EVSI were greater than the cost of collecting information applied in the prior information area, then collecting the failure data would be desirable; otherwise, collecting the failure data is not desirable.
(2) *Prior E{# of Failure}*: The expected number of failures for the remaining system lifetime under the status quo which is estimated by using the prior information only. This value shows the performance of the system if no risk reduction action is considered.
(3) *Prior decision*: The suggested decision is based only on the prior information. It could be either maintaining the status quo or undertaking the risk reduction action. If collecting the failure data is evaluated as not desirable, then the prior decision suggested by the DSS should be considered as the optimal decision.
(4) *Posterior E{# of Failure}*: The expected number of failures for the remaining system lifetime under status quo which is estimated by using both the prior information and the failure data. This value shows the performance of the system if no risk reduction action is

considered when the prior knowledge of the system and the failure data are both applied to evaluate the system.
(5) *Posterior decision*: The suggested decision is based on both the prior information and the failure data. It could be either maintaining the status quo or undertaking the risk reduction action. Once the failure data is applied, the posterior decision suggested by the DSS should be considered as the optimal decision.

Once the decision area shows the decisions suggested by the DSS, the decision maker can perform further analysis to ensure the suggested optimal decisions are reliable. Sensitivity analysis can show the degree of importance for each prior parameter and study how they affect the optimal decisions. The DSS can provide one-way sensitivity analysis by using each element in the prior information as the changing factor. The results would be the ranges of the prior parameters that are of special interest in which the optimal decisions remain unchanged. The DSS also provides what-if analysis by changing the values of the prior parameters in the prior information and see if the optimal decisions are still unchanged or not.

4. CONCLUSIONS

This proposed structural design of DSS for risk management of deterioration in physiological organs systems can provide decision support techniques not only for taking action in the light of all available relevant information, but also for maximizing expected profit (or minimizing expected loss). It can deal with uncertain prior knowledge about the physiological organs systems by considering the optimal prior decision, the sensitivity analysis, and possibly, the optimal posterior decision (if actual failure data were available), and provide decision makers the effective support for quality decision making.

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